VISUALIZED MOVEMENT PATTERNS AND THEIR ANALYSIS TO CLASSIFY SIMILARITIES – DEMONSTRATED BY THE KARATE KICK *MAE-GERI*

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Original scientific paper
UDC: 796.853.26:796.012.2:796.015.868

Abstract:

Single biomechanical parameters or characteristics cannot reflect the complexity of movements in sport. For this reason the paper introduces a procedure to visualize the movement pattern on the basis of the relevant movement angles to get a visual impression of the holistic movement. This procedure was applied to the karate kick *mae-geri* (front kick) which was executed by five athletes. By means of this method it was possible to identify similarities and differences in coordination between the movements of the individual karatekas. In addition, statistical analyses (coefficient of variability, Pearson's correlation coefficient and Euclidean distances) were used to confirm this and to determine the most stable angles in performance.

Key words: *biomechanics, movement pattern, coordination, karate, nonlinear approach, movement variability*

Introduction

Movements in sport are very complex, which leads to the case that biomechanical analyses must include a variety of kinematic and dynamic parameters and characteristic curves. Because of many quantities it is difficult to characterize movement stability respectively movement variability when conducting intra-subject and inter-subject comparisons. The attempts to quantify movement coordination as a whole are related to the following issues in movement and sports science:

- estimation of learning and training effects,
- determination of the influence of endurance on movement coordination during a load test,
- assessment of the movement stability on a training level,
- distinction between movements performed by either experts or novices,
- quantification of movement coordination with the purpose of movement optimization.

Because movement coordination is the result of numerous biomechanical characteristics and their interactions, special methods are necessary to describe any particular movement as a whole. For this purpose various holistic approaches and methods exist, the main purpose of which is the reduction of multidimensional datasets to only a few parameters that represent the properties of the system. These methods involve the application of the nonlinear system theory. Haas (1995) and Haken (1996), for example, used a synergetic approach to describe learning process of driving a pedalo. The synergetic approach and resultant determination of the system's parameters were applied to balance, walking and running (Witte, 2002; Witte, Bock, Storb, & Blaser, 2003) in order to quantify both stability and variability of movements. This usage of non--linear time series analysis would be a further possibility (Yamada, 1995; Newell, van Emmerik, Lee, & Sprague, 1993; Fahrig & Witte, 2007).

Another feasible technique of movement description is the application of artificial neural networks. Perl (2004) and Memmert and Perl (2009) used artificial neural networks to create movement patterns on the basis of angles. Schmidt, Fikus and Perl (2009) could verify the individuality of movement patterns at different levels of skill with such neural networks. Baca and Kornfeind (2010), for example, used this procedure in a study to measure the stability of biathlon shooting on the basis of the gun barrel movement's kinematic characteristics. Further examples for using neural networks for pattern analysis in sports are given by Lippold et al. (2004) and Jäger, Perl and Schöllhorn (2007).

Further important classes of movement performance analysis are known as projection methods which attempt to find the best approximating subspace in terms of data variance in order to project the system's dynamics. The principal components analysis (PCA) is a popular method, in part because it is numerically feasible for large dimensional systems (Sadeghi, Allard, & Duhaume, 1997; Braido, & Zhang, 2004; Wu, Wang, & Li, 2007). Besides this, the method is data-driven, meaning that the results are inherently a function of a specific data set. It can be declared that PCA is a technique for simplifying a dataset by reducing its dimensions for analysis. With the help of PCA, Mah, Hulliger and Lee (1994) studied gait patterns under different neurophysiological conditions on the basis of 15 body angles. Chen, Chuang and Zhuang (2008) applied PCA to classify short and long serves in table tennis.

Another conventional statistical method is cluster analysis. Lames (1994) could classify golf strokes and compared successfully his results with the results of a synergetic approach. The application of neural networks to movement parameters of tennis and volleyball serves performed by experts and novices reveals the essential meaning of sensory effects for movement control (Schack & Mechsner, 2006; Römer, Schöllhorn, Jaitner, & Preiss, 2003).

By means of PCA one can examine how the variance of a data vector is composed of the variances of single components. PCA transforms the data linearly to a new coordinate system so that the greatest variance by any projection of the data is transformed at the first coordinate (called the first mode), the second greatest variance at the second coordinate (called the second mode) and so on. This procedure was used to quantify gait patterns (Wu, Wang, & Li, 2007), to determine the influence of velocity on running coordination (Lamoth, Daffertshofer, Huys, & Beek, 2009), and to distinguish techniques of table tennis serves (Chen, Chuang, & Zhuang, 2008). It was also possible to classify different gaits in horseback riding through PCA. In addition, the influence of the saddle on movement coordination was studied and connected with a similarity analysis of the parameter's order (Witte, Schobesberger, & Peham, 2009).

Common to all the mentioned methods is that the reduction to one or a few parameters does not allow the consideration and analysis of the original parameters.

Therefore, the main aim of this study is the development of a holistic method which includes an integrated subjective observation of movement coordination. For this purpose the procedure of movement pattern plotting is proposed to obtain a holistic visual impression of movement coordination in its entirety. Further statistical analyses on the basis of the same biomechanical parameters provide the objectification of similarity among movements and the comparison within individual movement pattern plots. In this way movement similarities and differences can be found by a visual impression and validated by means of statistical procedures.

Based on this, the method has to meet the following requirements:

- individual impression of total movement coordination by movement pattern plots;
- application of statistical methods or tools to the movement - performance - relevant biomechanical characteristics in order to find similarities and differences between the movements.

The movement pattern plots are based on time courses of the normalized specific biomechanical parameters. In the first step it is necessary to select the biomechanical characteristics which are essential for movement performance. In most cases body angles are suited. This pattern permits a subjective overall impression of the movement. For the objective similarity analysis it is possible to analyze and compare the applied time courses of the biomechanical parameters by means of different statistical tools. These procedures allow an estimation of the stability behavior of specific biomechanical parameters.

This method is presented here with a complex movement pattern in sport, the karate kick *mae-geri*. The movement pattern was selected for the following reasons: this front kick is a complex whole-body movement but with no longitudinal rotations. From this a manageable number of biomechanical parameters can be obtained to describe satisfactorily movement coordination. In addition, it can be assumed that karate performance is automated on a high level, which implies a high individual stability (Witte, Emmermacher, Bystrzycki, & Potenberg, 2007).

Methods

Karate technique

In martial arts leg techniques are very often used because they give a higher rating in competition compared to arm techniques. Nevertheless, there are only a few biomechanical research studies of leg techniques (Kong, Luk, & Hong, 2000; Lee, Chin, & Liu, 2005; Witte, Emmermacher, Bystrzycki, & Potenberg, 2007; Emmermacher, Witte, Bystrzycki, & Potenberg, 2007). Kicks can be executed by either the front or back leg. In the present study only kicks performed by the back leg are considered. *Mae-geri* (Figure 1) is a front kick which begins by the knee brought up and forward with a stroked shank. Then the upper leg snaps forward towards the target (*keage* [Japanese], snapped variant) and the ball of the foot strikes the surface. The optimal body position during this movement is a vertical posture.

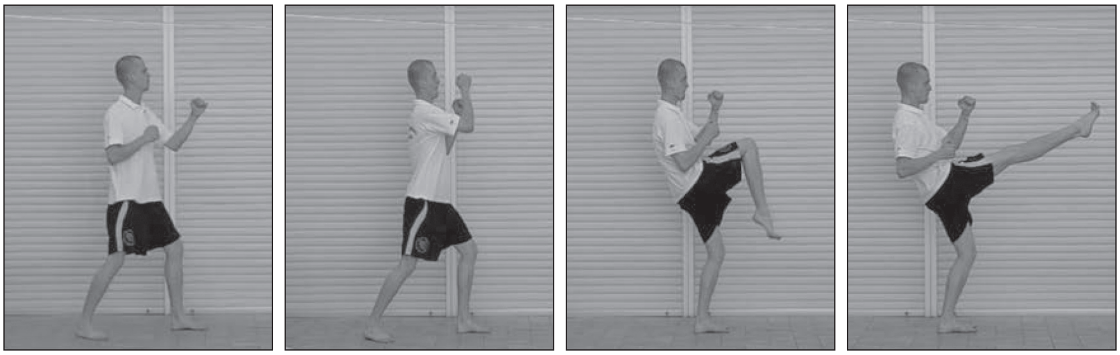

Figure 1. Mae-geri (front kick) with the back leg. From the left to the right:
• starting position: kamae; • longitudinal rotation of the trunk; • explosive knee movement upward, • snapping of the shank

Data recording

Five highly ranked national-level karatekas (aged 13–18 years) participated in this study - two male subjects: Chr and Joh, and three female subjects: Lui, Mar and Nad (Table 1). The technique (*mae-geri*) was performed ten times by each subject. The area *chudan* (i.e. solar plexus) was defined as the target.

The movement analysis was accomplished using VICON system (12 cameras MX-13, 250 Hz, Nexus V 1.01). In order to gain movement patterns the time courses of the body angles were exported.

General procedure to create movement pattern plots

For the creation of visual movement patterns the following procedures are necessary:

1. selection and normalization of biomechanical parameters relevant to a particular movement (e.g. body angles, angular velocities, forces etc.),
2. temporal normalization,
3. construction of a matrix containing movement parameters in discrete time lags,
4. visualization by means of contour plots in color or gray scales,
5. application of statistical methods or tools (descriptive methods, correlation analysis, or cluster analysis) for the normalized parameter time relations or the complete time courses.

Creation of movement pattern plots and applied statistical procedures

Table 2 shows an overview of the investigated movement-specific body angles. The selection re-

Table 1. Overview of the participating subjects

Subject	Gender	Age (years)	Body height (cm)	Body mass (kg)	Graduation / Qualification	Experience in competition
Chr	M	18	182	63	3rd kyu, German Champion	12 years, international, national
Joh	M	18	180	74	2nd kyu, 3rd place European Championship	10 years, international, national
Lui	F	18	168	63	2nd kyu, 2nd German Championship	10 years, international, national
Mar	F	13	160	50	5th kyu	4 years, international, national
Nad	F	15	172	59	4th kyu	6 years, national

Table 2. Body angles of mae-geri and use of the movement pattern plots and statistical analyses recording the Plug-in-Gait model by VICON

Number of the angle	Abbreviation of the angle	Name of the angle
W1	HipX	hip angle (flexion)
W2	Knee	knee angle (flexion)
W3	Ankle	ankle angle (dorsiflexion)
W4	Spine	spine angle (flexion/dorsiflexion)
W5	PelX	dorsiflexion of pelvis
W6	PelZ	internal rotation of pelvis

sulted from the empirical findings and expertise of long-time experienced trainers. The angle normalization can be accomplished with the following determinants: angle maximum 0 and angle minimum 1. For the absolute time scale of each movement performance the following temporal standardization was computed: 0, 0.1, 0.2,..., 1.0. Afterwards, a matrix containing movement parameters in discrete time-lags was constructed and visualized by contour plots in gray scales (Figure 2).

To quantify the body angles for each subject the variation coefficients were calculated. This was accomplished by computing each normalized time point, in sum 11 time points per angle. Additionally, the averaged correlation coefficients for each of the angles for all subjects were determined.

The next outstanding problem was to detect the temporal angle curves that showed the greatest similarities across all the observed athletes. Therefore, the Pearson correlation coefficients between all the

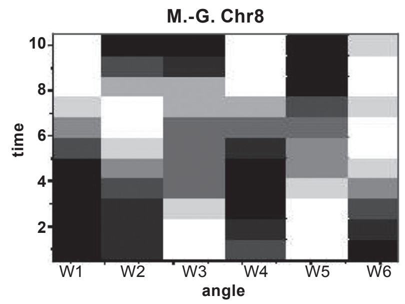

Figure 2. Example of a contour plot: mae-geri (subject Chr), movement Chr8. Meaning of the gray scale: white = angle maximum, black = angle minimum.

subjects for each angle were determined and from this the mean values were calculated.

Another method used to identify the similarities among the movement performances was the Euclidean distances. The results of this method show the most stable angles for each subject. More precisely, the Euclidean distances were calculated using the single angles between the executions for each subject. From this the similarity levels were defined (Table 4).

As the next procedure a weighted distance measure (WD), based on the previously calculated similar levels, was defined by:

$$WD=1\times N_I+2\times N_{II}+3\times N_{III}+4\times N_{IV}+5\times N_V+6\times N_{VI} \quad (1)$$

with $N_I \dots N_{VI}$ as the number of appeared rates in the single similar levels. The similar levels ($N_I \dots$, N_{VI}) were then weighted with factors 1 to 6. By means of this it was possible to compare two movements regarding their similarity for all the considered angles. The higher the number of the cases in the similar levels II–VI, the greater the parameter WD, so that, ultimately, the dissimilarity of the two movements increases. Lastly, all the movement performances of each subject were compared and ranked on the basis of the relation to the computed WD.

Results

Movement pattern plots

The Figures 3–5 show some examples of how each subject's movement patterns were visualized as contour plots. At first sight and with respect to the temporal successions of the gray scales, sub-stantial

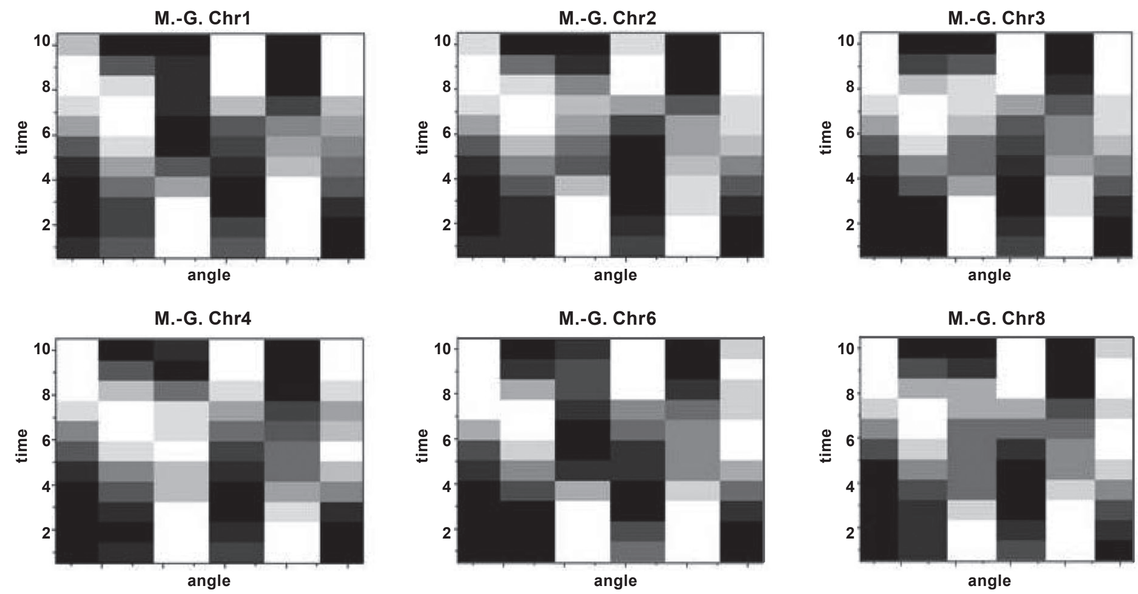

Figure 3. Visualized contour plots of the movement pattern of mae-geri for the athlete Chr (Chr1-Chr4, Chr6, Chr8): white = angle maximum, black = angle minimum. From the left to the right the angles W1 ... W6.

Table 4. Ranking of the executions regarding the movement duration (reverse scale) for the mae-geri performed by the subjects Chr, Joh, Lui, Mar and Nad. The number after the subject's name identifies the number of the execution (1 … 10 or 9)

Chr4	0.388	Joh10	0.488	Lui2	0.464	Mar9	0.464	Nad8	0.300
Chr9	0.392	Joh7	0.520	Lui1	0.480	Mar8	0,476	Nad1	0.340
Chr7	0.424	Joh3	0.524	Lui10	0.484	Mar1	0.480	Nad2	0.340
Chr5	0.428	Joh2	0.528	Lui3	0.488	Mar6	0.484	Nad3	0.340
Chr10	0.428	Joh4	0.528	Lui4	0.500	Mar3	0.492	Nad7	0.340
Chr3	0.436	Joh6	0.528	Lui8	0.500	Mar5	0.496	Nad4	0.360
Chr6	0.440	Joh5	0.556	Lui7	0.508	Mar7	0.512	Nad5	0.360
Chr8	0.448	Joh9	0.584	Lui9	0.520	Mar2	0.512	Nad6	0.360
Chr2	0.488	Joh8	0.608	Lui5	0.540	Mar4	0.516	Nad9	0.360
Chr1	0.536	Joh1	0.640	Lui6	0.540	Mar10	0.520		

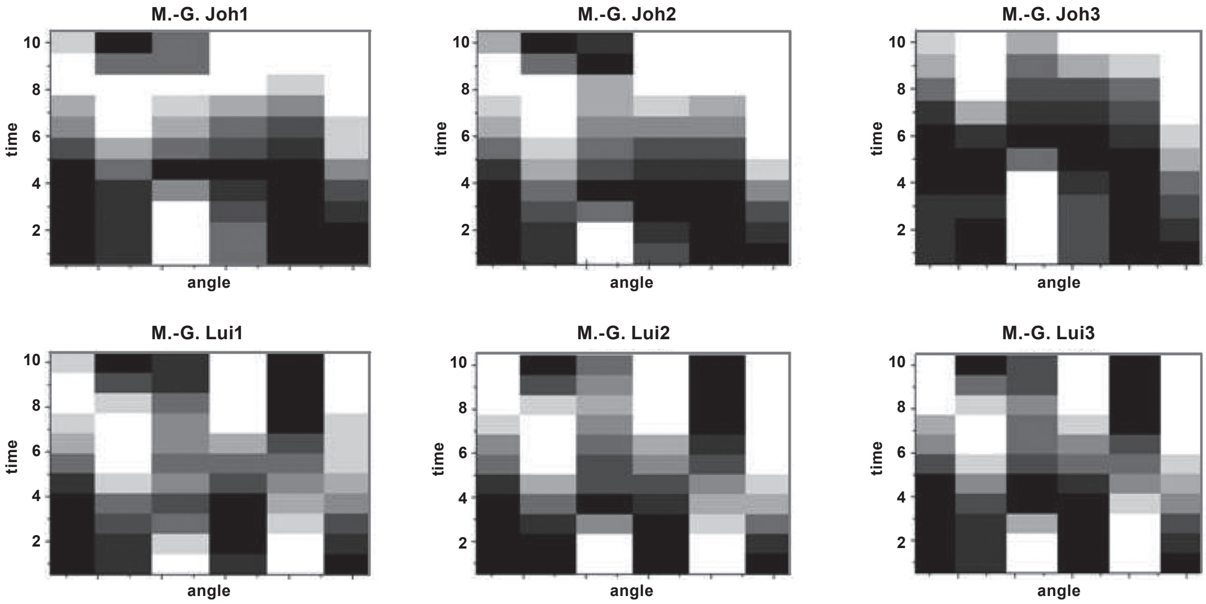

Figure 4. Visualized contour plots of the movement pattern of mae-geri for the athletes Joh (Joh1, Joh2, Joh9) and the athlete Lui (Lui1, Lui2. Lui3): white = angle maximum, black = angle minimum. From the left to the right the angles W1 … W6.

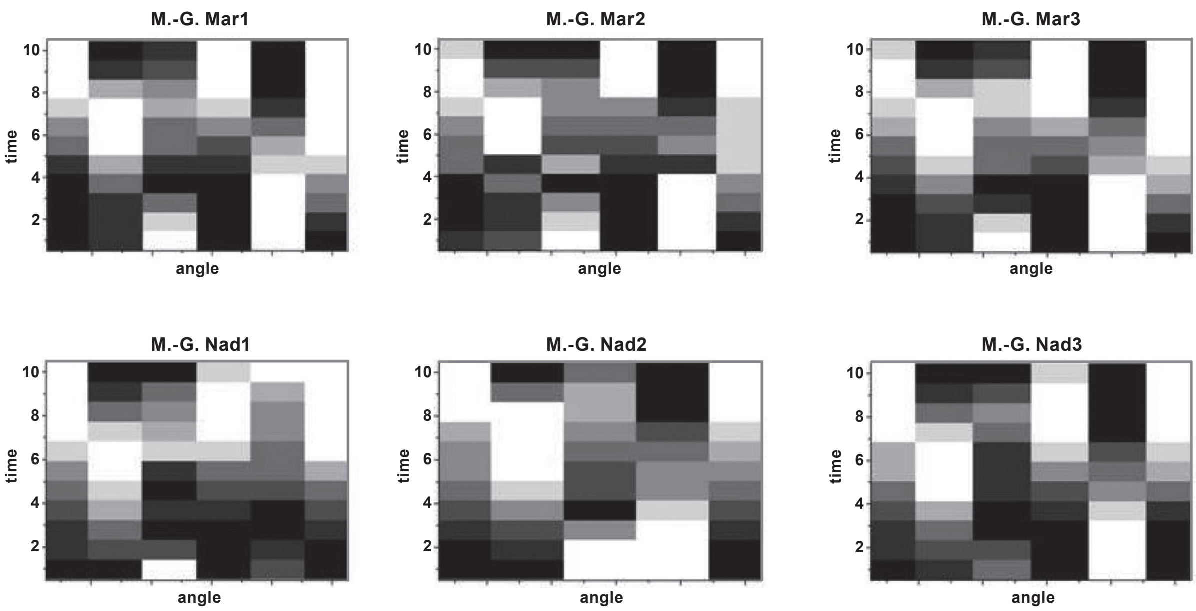

Figure 5. Visualized contour plots of the movement pattern of mae-geri for the athlete Mar (Mar1, Mar2, Mar3) and the athlete Nad (Nad1, Nad2, Nad3): white = angle maximum, black = angle-minimum. From the left to the right the angles W1 … W6.

similarities are visible for each subject. For example, subjects Chr and Lui exhibited similar characteristics regarding the hip angle (W1). Greater differences within individual athletes were observable for the dorsiflexion of pelvic angle (W5) of the subject Nad (Figure 5). It must be pointed out that only some executions are presented and the selection is unfortunately not absolutely representative of either the stable or variable movement behavior of each subject. The displayed plots in Figures 3–5 allow comparisons of the movement patterns for each subject and between the subjects. According to the patterns of Chr1 and Chr2 (Figure 3), the main difference was in the temporal behavior of the ankle angle (W3). Temporal properties of the other angles were analogue. Another example can be given for the subject Joh in Figure 4. For this athlete the different movement pattern of Joh9 in comparison to Joh1 and Joh2 was noticeable, but the trials Joh1 and Joh2 could be estimated as very similar. A comparison between Nad and the other subjects showed that she developed different and more variable movement patterns (Figure 5). In the displayed plots it can be seen that only the hip angle (W1) and the knee angle (W2) showed similar movement behaviors.

Determination of the individual movement variability

The stability behavior of the single angles was assigned by means of the coefficient of variability. The time-averaged variation coefficient for each angle and each subject is presented in Figure 6. It is apparent that the angles for each subject had a different behavior of variability. Thus, for the athletes Chr and Joh, the ankle angle (W3) was the most stable one. In contrast, for Lui, Nad and Mar (the ankle angle was the secondary stable angle) the knee angle (W2) was the most stable one. It could be concluded that the ankle angle (W3) and the knee angle (W2) can replicate itself most. In contrast, dorsiflexion of pelvic angle (W5) from Chr and Nad as well as the ankle angle (W3) from Mar displayed the greatest variations. When comparing all variation coefficients among the subjects, it could be concluded that the kicks executed by Mar and Lui showed the least variability. However, the most variable movements could be found for the athletes Joh and Nad.

Statistical procedures to quantify the similarity

The analysis by means of Pearson correlation coefficient should quantify the common variability behavior of the angles. Figure 7 shows that the lowest mean correlations (the greatest variations) exist for the dorsiflexion of pelvic angle (W5), ankle angle (W3) and spine angle (W4). From this it could be assumed that for the *mae-geri* the hip angle (W1), the knee angle (W2) and the internal rotation of the pelvis (W6) (here only a small amplitude is realized) were the most important angles.

The estimation of the stability of the angles for each subject was realized by the calculation of Euclidean distances and the generation of similarity levels (Table 3). In Figure 8 the percentage frequencies of the appearance of the similarity levels for each angle are represented. So, it can be established that for Chr, Lui and Mar the similarity level I for the hip angle (W1) occurred most

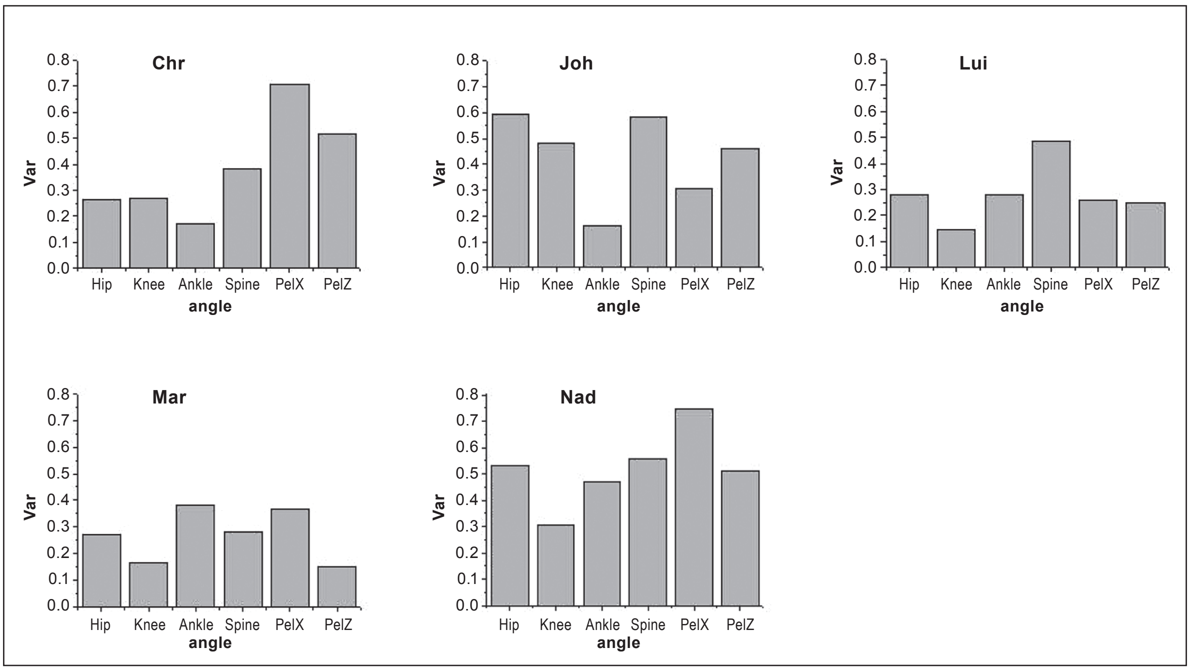

Figure 6. Averaged variation coefficients for each angle for all executions per subject.

Table 3. Definition of similarity levels on the basis of Euclidean distances

Similarity level	Range of Euclidean distances
I	0.0 – 0.2
II	>0.2 – 0.4
III	>0.4 – 0.6
IV	>0.6 – 0.8
V	>0.8 – 1.0
VI	>1.0

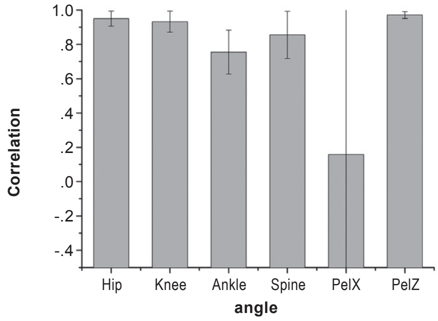

Figure 7. Averaged correlation coefficients of the particular angles across all the subjects.

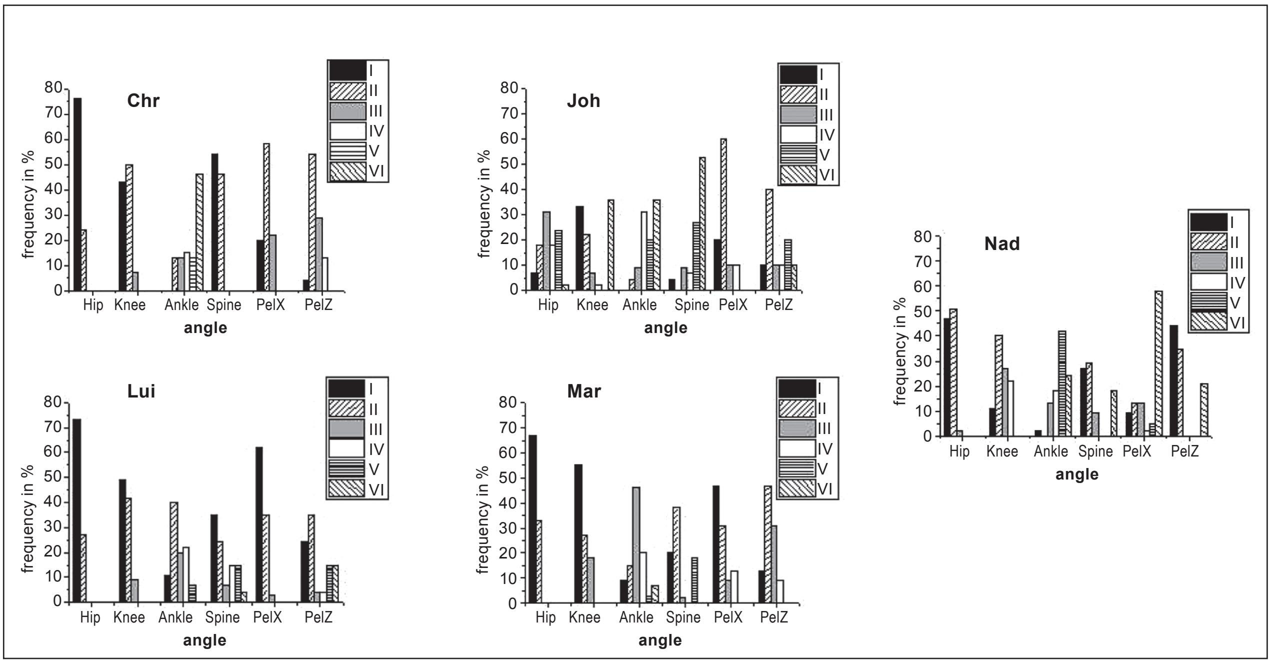

Figure 8. Percentage frequency of the appearance of the similarity levels I – VI for the particular angles.

frequently. The hip angle (W1) was characterized by a relative low variability (Figure 8). The high frequencies of similarity levels greater than similarity level II, which could be found in the subjects Joh and Nad, showed that there was no stable reproduction of these angles. It should be assumed that no explicit correlations between Euclidean distances and variation coefficients existed.

Comparison between movement coordination and movement velocity

The following consideration should demonstrate a potential field of application of the movement pattern analysis in connection with other biomechanical parameters. Thus an interesting aspect is the velocity of movement. Table 4 shows the order of the executions in relation to the movement time measured by video analysis. Corresponding to Table 4, the trials Chr1 and Chr2 were the slowest movements of the subject Chr. They were also characterized by similar movement pattern plots (Figure 3). However, no general differences in relation to the fastest movement Chr4 were found. On the other hand, duration times of the movement performed by the subject Nad (Table 4) were nearly equal, although even this athlete had demonstrated very different movement patterns.

It can be concluded that in some cases the visualized contour plots with additional variation analyses gave indications of recording the speed of movements. But the visualized contour plots could not clearly identify the fastest and the slowest movements.

By using the weighted distance measure (WD) in relation to the movement duration, the following findings could be made. With reference to the slowest trial of the subject Chr (Chr1), most of the other movement performances were very dissimilar. It was found that Joh8, which was the second slowest movement, differed most from other movements (WD = 15…17). However, a relatively high similarity between the fastest and the slowest execution was determined. For the subject Lui in relation to Lui1, Lui2 and Lui10 (the fastest and the most dissimilar movements) and in contrast to the other trials the highest values for WD were calculated. The slowest movements Lui5 and Lui6 were very similar to each other (WD = 8). The fastest trials of the subject Mar (Mar9, Mar8 and Mar1) were not very similar to each other and were shown separately. For the subject Nad the most similar executions were neither the fastest nor the slowest movement performances. For the second slowest movement (Nad6) relatively high values of WD were computed. The results implied that no clear correlations existed between coordination and movement velocity.

Discussion and conclusions

It could be demonstrated that the introduced procedure allowed a first estimation of coordination by means of visual impressions. Additional information about the temporal course of single biomechanical parameters, particularly body angles as well as the variability of the movement coordination can be given using statistical methods.

As an example of a movement the karate kick *mae-geri* was used. This karate kick could be characterized by means of time courses of six movement-relevant angles. The normalization of the angles and the duration time enabled the comparison between different executions of one subject and between the athletes.

It should be noted here that with an increased number of angles the visual movement pattern would become more confusing. Therefore it is important to use only a limited number of the movement-characteristic parameters. Another issue is the determination of the necessary but sufficient number of discrete time points, which in our case, were eleven time points. The discrete angle-time-series could also be used for other analyses:

a) determination of averaged variation coefficients for each angle across all executions per subject,
b) determination of averaged correlation coefficients for the single angles across all the subjects,
c) calculation of the percentage frequency of the appearance of the similarity levels on the basis of Euclidean distances.

Generally, the results of these statistical methods are in accordance with the subjective impression of the visual movement patterns. For many movement cases there has not been a decision which movement parameters are the most important ones. A variation analysis could help to find these parameters. With this it is possible either to label these columns in the pattern or to order them first.

By means of the procedure of creating the visual movement pattern and the use of the methods a)-c) some results recording the similarity of the

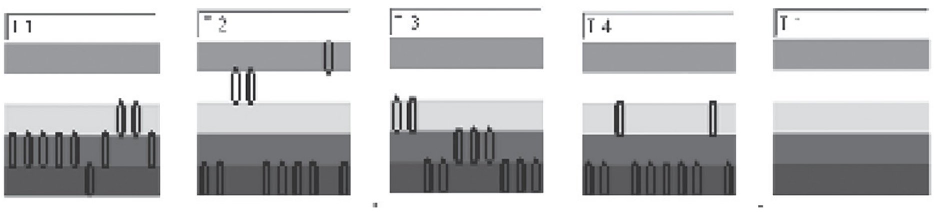

Figure 9. Results of the network analysis after Perl (2004) for the mae-geri. From the left to the right: Chr, Joh, Lui, Mar and Nad. Each movement is marked by a circle. The most similar movements are located at the same level. The distance between the levels is a measure of dissimilarity.

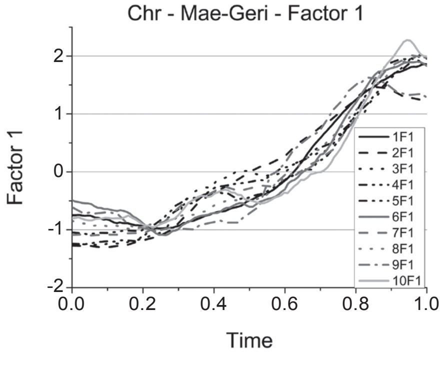

Figure 10. Results of PCA for the subject Chr. The diagram shows the temporal courses of the load values of factor 1.

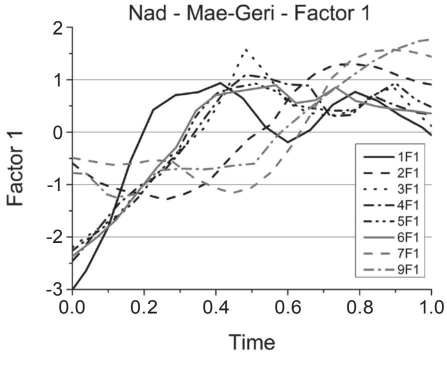

Figure 11. Results of PCA for the subject Nad. The diagram shows the temporal courses of the load values of factor 1.

karate kick *mae-geri* could be found. The subjects were able to repeat the movement with a similar coordination. The angles with a high stability in repetitions (hip angle, knee angle, internal rotation of pelvis) and the angles with a high variability (ankle angle, dorsiflexion of pelvis) were found. From this it can be assumed that stable angles are important to the process of learning this movement. The determination of mean correlation coefficients for the single angles over all the subjects confirmed this. The calculation of the percentage frequency of the appearance of the similarity levels on the basis of the Euclidean distances allowed an individual and detailed analysis of the variation of the single angles. The definition of similarity levels allowed a sophisticated consideration of the ability to reproduce the single angle-time-curves for each subject. Based on this, advice for an optimization of the training process could be made. The definition of a weighted distance measure allowed one to compare all the single executions with each other. By an influenced weighting of the single similarity levels an individual comparison recording the similarity or dissimilarity is possible. This quantification can be used to find correlations to other performance parameters. For example, we tried to find a relation between movement coordination and movement velocity. In some cases it was found that the fastest as well as the slowest movement performances were different in their coordination from the other movements. However, a clear correlation could not be found. That means that the movement coordination is only one factor which influences the movement velocity. Other parameters such as the velocity of the individual body segments were not determined or considered. This again implies that similar movements can vary in their velocity.

For a comparison with other holistic approaches, the results of the neural network analysis by Perl (2004) and of the principal components analysis (PCA) are presented in Figures 9–11. In the case of the neural network analysis, smaller temporal distances were determined, so that each movement was characterized by 31 time points. The most similar movements were located at the same level, which is illustrated by a specific gray scale (Figure 9). The trials of the subject Nad were an exception; the neural network could not find similar movement patterns. Furthermore, the movements of Nad differed strongly from the movements of the other subjects in terms that they were not marked in the neural network diagram (fifth diagram in Figure 9). In other words, no similarity was found between the executions of Nad in comparison to the kicks executed by the other athletes. The next two examples showed equal results as the movement patterns. The special position of Chr6 (neural network, Figure 9) could be recognized in the visual movement pattern (Figure 3). For the subject Joh the examples of the movement patterns in Figure 4 clarified in analogy to the neural network analysis (Figure 9) the great difference between the trial Joh9 compared to the other ones. Because of the different approaches of the movement patterns, statistical tools and the neural network analysis, absolutely identical results cannot be expected.

The PCA was carried out exemplarily for the subjects Chr and Nad. From these results (Figures 10 and 11) it could be concluded, that the temporal courses of the load value of factor 1 for the subject Chr were very similar. Differences between single trials could be found for the subject Nad. These results agree in principle with the visual movement patterns and the results from the statistical procedures.

It can be concluded that the introduced method to produce visual patterns allows a subjective perception of the total movement coordination and that the patterns can give an orientation for assessment of stability of movement coordination. A detailed statistical analysis to estimate the variability or similarity of the movement coordination can complete the subjective perception of the movement pattern.

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VIZUALIZIRANI KRETNI OBRASCI I NJIHOVA ANALIZA ZA KLASIFIKACIJU SLIČNOSTI – PREDSTAVLJENO NA PRIMJERU KARATE UDARCA *MAE GERI*

Mnogi se problemi u kineziologiji vezuju za koordinaciju pokreta. Pojedinačni biomehanički parametri ili karakteristike ne mogu, međutim, ocrtati svu složenost pokreta u sportu. Zbog toga ovaj članak predstavlja proceduru za vizualizaciju obrasca kretanja na osnovi relevantnih kretnih kutova s ciljem da se dobije vizualni prikaz, otisak cjelovitog pokreta (holistički pristup). Postupak je primijenjen na karate udarac *mae-geri* (udarac nogom prema naprijed) koji je izvodilo pet sportaša. Predloženom metodom bilo je moguće identificirati sličnosti i razlike među kretnjama svakoga karataša. Štoviše, statistička analiza (koeficijent varijabilnosti, Pearsonov koeficijent korelacije i euklidska udaljenost) bila je primijenjena za potvrdu i utvrđivanje najstabilnijih kutova u višekratnim izvedbama strukture kretanja.

Ključne riječi: *kretni obrasci, koordinacija, karate, nelinearni pristup, pokret*

Submitted: June 26, 2010
Accepted: October 31, 2011

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